Assessing Carbon Dynamics in Agriculture Using Remote Sensing

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1. Introduction

Increasing atmospheric concentrations of CO_2 and other greenhouse gases is a global concern. Agricultural activities contribute to CO_2 and N_2O emissions through combustion of fossil fuels, soil organic carbon (SOC) decomposition, and biomass burning. Although green plants convert CO_2 into carbohydrates and biomass, most of the CO_2 that green plants absorb reenters the atmosphere through respiration of plants and animals and through microbial decomposition.

Depending on land use and management, soil can function as either a source or sink for atmospheric CO_2. Based on the large decreases in soil organic carbon when native forests and grasslands were converted to agriculture, the potential for C sequestration in soils is very large (Lal et al., 1999). Carbon can be stored in the soil in either living organisms or in their residues in a form which resists further biological degradation. Models can predict net carbon sequestration for different soil types and land management.

Numerous models of C dynamics have been published and range from complex research-oriented models to simple empirical applications-oriented models (Ma and Shaffer, 2001). The complex research models emphasize the underlying biological, chemical, and physical processes that control C flows, but tend to be point-based because of their detailed input data requirements. The simple empirical models correlate ecosystem-scale processes with parameter that are readily measured in the field and, as a result, may gloss over some important functional relationships.

The linkage of process models to geographic information systems (GIS) for spatially distributed fields or watersheds has blurred the spatial scale distinction between research and application models. Lack of data to support these process models across a wide range of soil and land management scenarios continues to be a major issue limiting their usability. Robust approaches for extending C models from local to regional and global scales have not been identified and evaluated. Recent advances in remote sensing of vegetation and soils can potentially provide some of the biophysical parameters needed by various C models to predict C dynamics across landscapes.

In this paper, we briefly 1) review current status for remote sensing of crops and soils, and 2) examine the potential role of remote sensing for assessing C dynamics in agriculture.

2. Remote sensing of crop production

When solar radiation interacts with matter, it may be reflected, transmitted, or absorbed. The spectral reflectance of crop canopies is determined by 1) leaf spectral properties, 2) leaf area index (LAI) and canopy geometry, 3) background (soil or residue) reflectance, 4) illumination and view angles, and 5) atmospheric transmittance (Bauer, 1985). When vegetation density is low, background reflectance significantly influences canopy reflectance. When vegetation density is high, leaves are the primary scattering elements and the background contributes little to overall canopy reflectance.

The spectral properties of leaves are determined by the concentration of chlorophyll and other pigments in the visible (400-700 nm) wavelength region, by mesophyll structure in the near infrared (700-1200 nm) region, and by amount of water in the middle infrared (1200-2400 nm) region (Knipling, 1970). As leaves expand, mature, and senesce, physiological and morphological changes occur that effect their spectral properties. Various stresses, including nutrient deficiencies, water deficits, and damage by insects and diseases, also affect the optical properties of leaves (Walter-Shea and Biehl, 1990).

Crop identification and area estimation were major thrusts of U. S. agricultural remote sensing programs such as the Corn Blight Watch Experiment (MacDonald et al., 1972), and the Large Area Crop Inventory Experiment (LACIE; MacDonald and Hall, 1980). These programs firmly established the feasibility of using multispectral scanner data and digital analysis techniques to identify and estimate the areal extent of crops. These programs also recognized the importance of multi-temporal remotely sensed data for consistent, accurate crop identification.

The crop is the ultimate integrator of its environment and the spectral appearance of the crop contains useful information on its condition and potential yield. Although spectral reflectance has been directly related to biomass, LAI, and yield of crops, the relationships are seldom robust. Temporal changes in spectral reflectance, particularly the normalized difference vegetation index (NDVI), have been related to absorbed photosynthetically-active radiation (APAR; Asrar et al., 1989), to net primary production (Prince, 1991), and to grain yields (Gallo et al., 1985).

Crop models that simulate biophysical processes in the soil-plant-atmosphere system can provide nearly continuous (i.e., hourly, daily) descriptions of crop growth and development. Ideally, a system for assessing crop condition and yield would combine the superior temporal resolution of the physiological crop models with the superior spatial resolution of remotely sensed data.

Two distinct approaches have been used to incorporate remotely sensed data into crop growth models. In the first approach, crop biophysical characteristics are estimated using remotely sensed data and input directly into the growth model. Typically, spectral estimates of the fraction of absorbed radiation or leaf area index (LAI) were incorporated into the growth models (Daughtry et al., 1983). These relatively simple models are based on the assumption that biomass production is a function of the amount of radiation absorbed by the crop (Kumar and Monteith, 1981). Environmental stresses that reduce biomass production may not be explicitly accounted for in these simple models.

In the second approach, a time series of remotely sensed measurements is used to calibrate the crop growth model. For example, Maas (1988) periodically adjusted the LAI values simulated by crop growth model to match the LAI values estimated from the reflectance data. One limitation of this approach is that the relationship between reflectance and LAI must be determined empirically for each location. Alternatively, LAI may be estimated by inverting a radiative transfer model, such as SAIL (Verhoef, 1984) and then incorporated into the crop model. The inversion required remotely sensed data that had been radiometrically corrected for atmospheric transmittance plus estimates of leaf optical properties, canopy geometry, and background reflectance. Using this approach, Doraiswamy et al. (2001) successfully simulated LAI for various crops using multi-temporal satellite data and then incorporated the simulated LAI in models to predict grain yields.

3. Remote sensing of soil properties

The spectral reflectance of soils is determined by physical factors quite different from those of vegetation. Soil reflectance generally increases with increasing wavelength. The relative contributions of moisture content, iron-oxide content, organic matter content, particle-size distribution, mineralogy, and soil structure to reflectance of naturally occurring soils have been throughly reviewed (Baumgardner et al., 1985; Irons et al., 1989). In perhaps the most comprehensive study of the reflectance of soil, Stoner and Baumgardner (1981) defined five general classes of soil reflectance spectra. Organic matter content and iron oxide content were the primary factors determining shape of the reflectance spectra. In general, soil reflectance increased as soil moisture, particle-size, surface roughness, organic matter content, and iron oxide content decreased. Spectral reflectance is strongly correlated with soil organic matter among soils from the same parent materials; however, the relationship is sensitive to changes in iron and manganese oxides in soils form different parent materials (Henderson et al., 1992).

Remote sensing as aerial photography has been a tool in the mapping of soils. The synoptic view of the soil in the landscape and the tonal variations in the photographs enhanced the delineation of soil boundaries and identification of inclusions within the predominant soil series. Multispectral images have also been used to aid soil survey, soil inventory, and soil management (Baumgardner et al., 1985).

Important soil properties for crop growth related to water holding capacity and fertility can be indirectly estimated by remote sensing of vegetation (Walthall et al., 2001). Spatial patterns in remotely sensed images and crop yield maps over several years have been analyzed to identify areas within fields with similar crop responses (Gish et al., 2002). These homogenous zones may be used to guide soil sampling and form the basis for adjusting nutrient application rates using variable rate technology.

4. Remote sensing of crop residues

Crop residues are the portions of a crop that is left in the field after harvest. Shortly after harvest, crop residues are frequently much brighter than the soil, but as the residues weather and decompose they may be either brighter or darker than the soil (Nagler et al., 2000). The reflectance spectra of both soils and crop residue lack the unique spectral signature of green vegetation in the 400 to 1000 nm wavelength region (Aase and Tanaka, 1991). Crop residues and soils are often spectrally similar and differ only in amplitude at a given wavelength (Baird and Baret, 1997). This makes discrimination between crop residues and soil difficult or nearly impossible using reflectance techniques in the visible and near infrared wavelengths.

One promising remote sensing approach for discriminating crop residues from soil is based on a broad absorption band near 2100 nm that appears in all compounds possessing alcoholic -OH groups, such as sugars, starch, and cellulose (Murray and Williams, 1988). This absorption feature was clearly evident in the reflectance spectra of the dry crop residues, but was absent in the spectra of the soils (Daughtry, 2001). The relative depth of this absorption feature using reflectance in three bands - two on the shoulders at 2021 and 2213 nm and one at 2100 nm (absorption maximum) defined a cellulose absorption index (CAI). Moisture content, age of the residue, and degree of decomposition affected the spectral reflectance and CAI of crop residues (Nagler et al., 2000). Water significantly altered the reflectance spectra of wet crop residues, but did not prevent the discrimination of crop residues from soils using CAI.

Crop residue cover is linearly related to CAI (Figure 1). Less than 10% green vegetation cover in the scene had little effect on CAI, but as green vegetation cover in the scene increased, the errors for estimating crop residue cover using CAI increased. Water in green vegetation attenuated the cellulose absorption feature near 2100 nm and reduced the CAI value in a similar manner that water reduced the CAI values of crop residues (Daughtry, 2001). Research is underway to evaluate both AVIRIS and Hyperion images for assessing crop residue cover using the CAI approach.

5. Remote sensing of soil tillage

Tillage hastens carbon oxidation by increasing soil aeration and soil-residue contact and accelerates soil erosion by increasing exposure to wind and rain. A large proportion of soil organic carbon content is concentrated near the soil surface and is highly vulnerable to oxidation and soil erosion. Tillage practices strongly influence the fate of soil carbon.

Conservation tillage is any tillage and planting system that maintains at least 30% of the soil surface covered by residue after planting (CTIC, 2000). Crop residue management is an integral part of any conservation tillage system and includes selecting crops that produce sufficient quantities of residues and sowing cover crops to provide an effective ground cover. Long-term use of conservation tillage can lead to increased SOC content, improved soil structure, and increased aggregation compared with plow-tilled soils (Rasmussen and Rohde, 1988).

Efforts to identify tilled fields using changes in surface reflectance have had mixed success (e.g., Baird and Baret, 1997; van Deventer et al., 1997). Although tillage frequently roughens the soil surface and decreases soil reflectance, the effect is short-lived and reflectance may increase as the soil surface is smoothed by rain or subsequent tillage. However, if tillage categories are defined by the amount of residue cover, it may be possible to use CAI identify tillage categories. The conservation tillage has been defined as any tillage and planting system that has more than 30% residue cover after planting; reduced-tillage as15-30% residue cover; and intensive or conventional tillage as less than 15% residue cover (CTIC, 2000). The two dashed horizontal lines in Figure 2 divide the feature space into these three tillage categories and the vertical dashed line is related to green vegetation cover. The ability to identify tillage systems using remotely sensed images could be crucial input for assessing spatial variability of carbon dynamics across agricultural landscapes. Regional surveys and maps of crop residue cover and conservation tillage practices may be feasible using hyperspectral imaging systems.

6. Potential remote sensing inputs to C models

Remote sensing techniques can not directly monitor soil carbon dynamics; however, remote sensing can provide a number of crucial inputs to carbon models. Figure 3 shows the simplified, conceptual flow of organic carbon through various pools in a generic soil carbon model. Briefly, the gross primary production of green plants is partitioned between above ground and below ground plant components. After subtracting the respiratory costs, above- and below-ground net primary production (NPP) are determined. For a typical annual crop, some fraction of the above-ground NPP is harvested yield and the remainder is left in the field as surface residue; all of the below-ground NPP becomes subsurface residue. As both the surface and subsurface residue break down, labile carbon is absorbed into the active pool of soil organic matter (SOM), whereas structural carbon is transferred to the slow SOM pool. During turnover of the slow SOM pool, some SOM becomes recalcitrant and transferred to the passive SOM pool. Net N mineralization results from the turnover of all three pools of SOM and the decomposition of surface and subsurface residues. Fertile soils with high SOM generally have high net N mineralization, which in turn can either be taken up by plant roots to enhance gross primary production or leached from the soil system.

Direct inputs to soil carbon models, that can be determined by remote sensing imagery, are associated with above-ground NPP and include land use, crop type, crop phenology, LAI, and APAR. Tillage practices and soil surface residues also may be determined directly by advanced (hyperspectral) remote sensing techniques. Additional inputs may be derived indirectly by examining the feedback between soil fertility and gross primary production as a means for updating the SOM dynamics in the models. The differences between expected soil fertility and crop growth will highlight specific areas in fields that need to be sampled and evaluated. These inputs for soil carbon models, when implemented within a geographic information system (GIS), will provide important boundary conditions on the amount and dynamics of SOM across landscapes.

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List of Figures

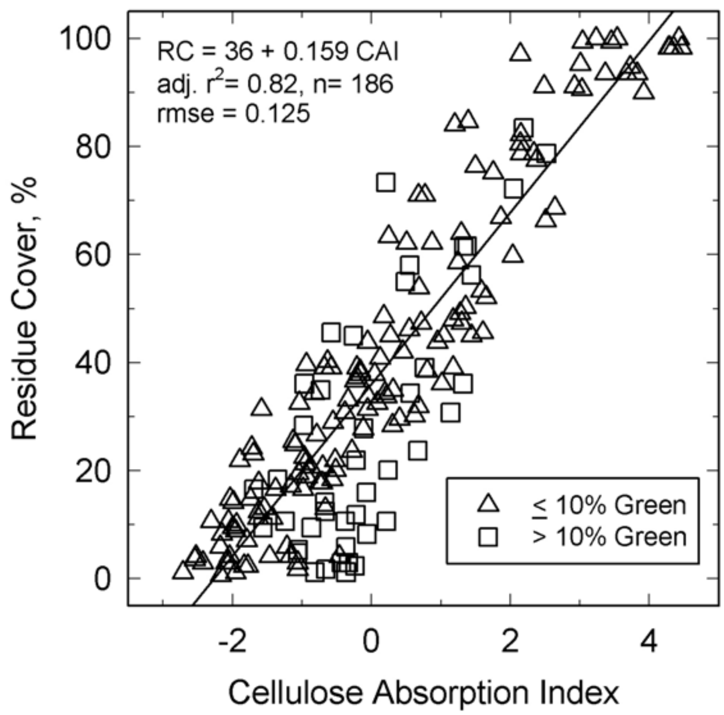

Figure 1. Fraction of crop residue cover as a function of cellulose absorption index (CAI) in corn fields after planting. The fractions of green vegetation (f_G) in the scenes are indicated by the symbol type.

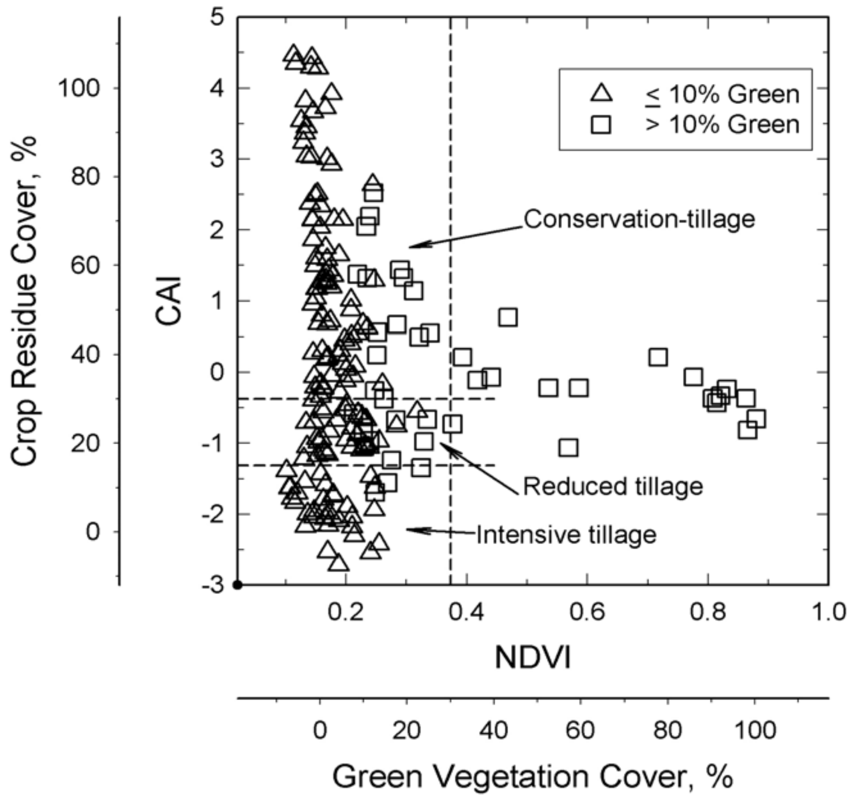

Figure 2. Scatterplot of CAI and NDVI for scenes in a corn field after planting. The horizontal dashed lines indicate 15% and 30% residue cover. Conservation tillage is defined as having more than 30% residue cover after planting; reduced-tillage has 15-30% residue cover; and intensive or conventional tillage has less than 15% residue cover.

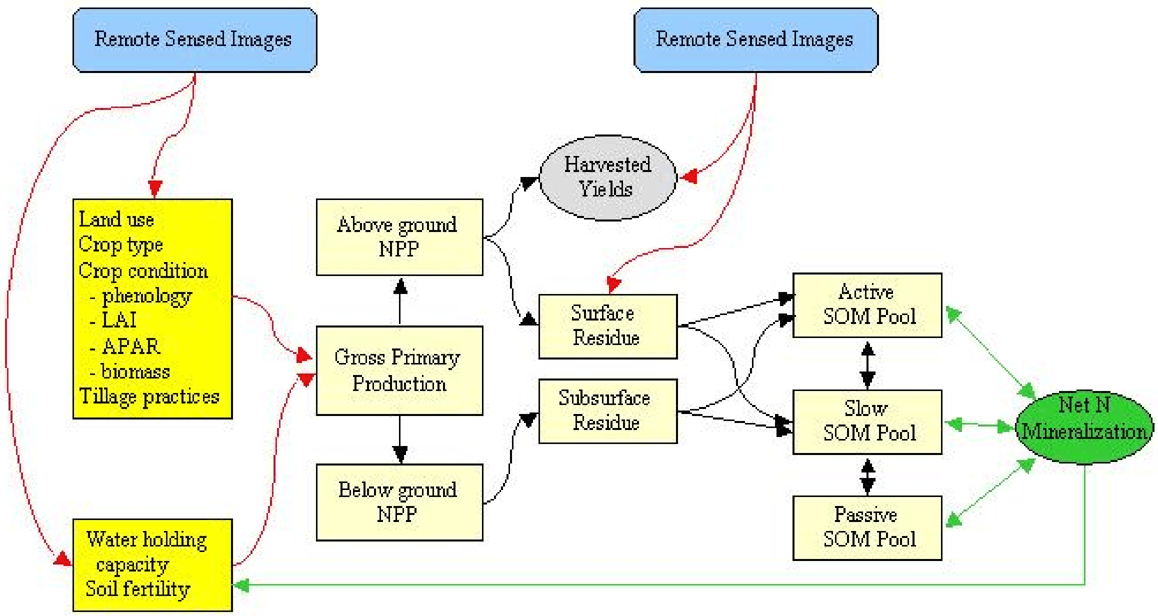

Figure 3. Conceptual flow of organic carbon through various pools of a generic carbon model. Remote sensing technology can provide site-specific information for agricultural fields for implementing carbon models across landscapes.